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AI-DRIVEN MULTI-OBJECTIVE UAV ROUTE OPTIMIZATION

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ABSTRACT

Unmanned Aerial Vehicles have proven to enhance customer service and increase efficiency in supply chain management. They offer greater flexibility, ease of operation, and bypass traffic congestions by flying directly between nodes. This paper presents an innovative version of the Team Orienteering Problem with Time Windows and Charging Stations. The proposed model integrates various optimization approaches, including heuristics and AI-driven methods. The primary objectives are to maximize service rewards, minimize total travel distance, and mitigate out-of-charge incidents. Experiments are conducted to demonstrate the competency of the applied AI-enabled approach in various scenarios.

1 INTRODUCTION

Unmanned Aerial Vehicles (UAVs) have many advantages such as being able to fly from one location to another directly, extra flexibility in extreme environments and requiring much less human labor to operate and maintain. Such advantages make UAVs a viable option for a wide range of problems. Many applications have been found for UAVs, including search-and-rescue operations for locating avalanche survivors (Wolfe et al. 2014), collecting research data and images (Newman, David L 2014), agricultural surveillance and decision support (Herwitz et al. 2004), urgent healthcare item delivery (Scott and Scott 2019), power line and pipeline inspections (Smith 2015), animal migration monitoring (Borrelle and Fletcher 2017), and farming in areas inaccessible to ground-based machinery (Wang et al. 2019). These examples illustrate the ever-increasing usefulness of UAVs. It can be seen from such examples that the fast-growing utilities of UAVs will certainly make them a game-changer in supply chain management.

Although UAVs come with many advantages, they also carry with them some limitations. A critical limitation of the current use of UAVs is represented by the lack of aerial refueling capabilities (Fravolini et al. 2004). UAVs' power source has limited capacity which hinders their further implementations. This limitation also drastically increases the risk of the UAVs running out of charge and falling down. Such a case, once it happens, will result in a significant increment in the costs of the service providers. Many kinds of research are conducted to solve this problem, including the development of an IoT-based automated landing system (Chae et al. 2015), an automatic battery replacement mechanism (Fujii et al. 2013), an electromagnetic field associated with utility power lines (Silberg, Eric J and Milgram, Judah H 2010). As a result, It's important to consider charging methods when optimizing UAV routes.

To briefly summarize, the inspirations of this research are i) the promising future of the utilization of UAVs in supply chain management; ii) the urgency of including charging methods as an essential part of the optimization. This study focuses on an innovative variant of the *Team Orienteering Problem* (TOP) that takes into account the UAVs routing problem with charging stations. As shown in Figure 1, at the beginning of the time frame, a fleet of homogeneous UAVs depart from the hub (depot) to serve the customers and collect the rewards. At this point, UAVs' battery is fully charged upon their departure. Several charging stations are located in the working area. The power is consumed uniformly on the way between locations (nodes and charging stations). If, upon finishing serving a node, the remaining power of a UAV is less than the threshold, its next destination will be the nearest charging station. After getting fully charged again, it immediately continues its work until the next time it needs charging. Due to the limited battery capacity and time frame, not all the nodes are visited. Therefore, it is required to figure out the optimized sequence of locations (nodes and charging stations) for each UAV.

This paper explores four different approaches to address the orienteering problem for UAVs with limited battery capacities. The approaches include two heuristic methods, Simulated Annealing (SA), and a novel integration of SA with Neural Networks (SA-NN). Each technique is applied to optimize the routing of UAVs, taking into account the constraints of battery life and operational efficiency. A set of experiments are conducted to compare these methodologies, emphasizing their unique advantages and practical applicability.

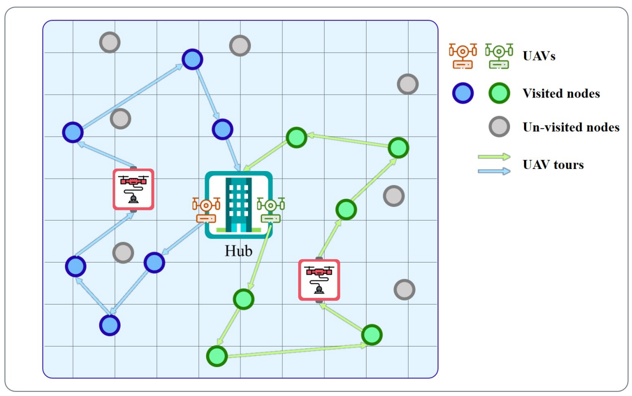

Figure 1: A fleet of two identical UAVs depart from the hub to visit service nodes, continuously visiting nodes until their battery level drops below a pre-defined threshold. If necessary, the UAVs will travel to the nearest charging station to wait for their battery to be fully charged before continuing to visit nodes. At the end of the time frame, the UAVs return to the hub. Some nodes may not be visited due to low reward or long distance.

2 LITERATE REVIEW

The term *TOP* was firstly carried out in 1996 (Chao et al. 1996), but a TOP was researched as Multiple Tour Maximum Collection Problem (MTMCP) in as early as 1994 by Butt and Cavalier (Butt and Cavalier 1994). Many efficient algorithms were introduced in the following years, such as column generation (Butt and Ryan 1999), branch-and-price algorithm (Boussier et al. 2007), ant colony optimization (ACO) (Ke et al. 2008) and tabu search (TS) (Tang and Miller-Hooks 2005b). The research achievements are summarized by Vansteenwegen et al. (Vansteenwegen et al. 2011). In this chapter, the review of literature is roughly categorized into deterministic and stochastic problems.

2.1 Deterministic Problems

Sevkli and Sevilgen proposed a solution to an Orienteering Problem (OP) by using a strengthened version of particle swarm optimization (PSO) (Sevkli and Sevilgen 2010) and a discrete strengthened particle swarm optimization (DPSO) (ŞEVKLİ and SEVİLGEN 2010). Chekuri et al. tackled the OP using approximation algorithms (Chekuri et al. 2012), while Liang et al. introduced Multi-Level Variable Neighborhood Search (MLVNS) to solve it (Liang et al. 2013). Campos et al. proposed the use of Greedy Randomized Adaptive

Search Procedure (GRASP) and Path Relinking to solve the OP (Campos et al. 2014), and Grasas et al. developed a simheuristic framework that combines a metaheuristic component with simulation methods for finding the optimal solution (Grasas et al. 2016). Poggi et al. used branch-cut and price techniques to tackle a Team Orienteering Problem (TOP) and introduced an extended formulation that indexes edges by the time they are placed in the route (Poggi et al. 2010). Bouly et al. proposed a memetic algorithm for TOP that uses a simple hybrid genetic algorithm with specific algorithms designed for the problem (Bouly et al. 2008). Muthuswamy et al. developed the first known DPSO algorithm to solve the 2, 3, and 4-member TOP (Muthuswamy and Lam 2011). Lin et al. introduced a simulated annealing with restart strategy (SARS) heuristic to solve the multi-constraint team orienteering problem with multiple time windows (MC-TOP-MTW) (Lin and Vincent 2015).

2.2 Stochastic Problems

Teng et al. introduce and solve the time-constrained traveling salesman problem with stochastic travel and service times (TCTSP) (Teng et al. 2004). Related to the TCTSP is the stochastic selective travelling salesperson problem (SSTSP) introduced by Tang and Miller-Hooks (Tang and Miller-Hooks 2005a). Over the years, a lot of other methodologies have been applied to tackle the problem, like an ILS-based approach to solve the uncapacitated facility location problem (de Armas et al. 2017), a hybrid local search and simulated annealing (Hu and Lim 2014), a hybrid greedy randomized adaptive search (Labadie et al. 2011), a Monte Carlo sampling and Hybrid Monte Carlo sampling and an analytical solution (Papapanagiotou et al. 2014), a combination of biased-randomization techniques and Monte-Carlo simulation (Reyes-Rubiano et al. 2018), a simheuristic algorithm is proposed as a solving approach integrating simulation inside a multi-start heuristic framework (Fajardo et al. 2018), a Stochastic profits by exact solution algorithm and bi-objective genetic algorithm. (Ilhan et al. 2008), a stochastic time-dependent travel times with mixed integer linear programming-sample average approximation (Varakantham and Kumar 2013), a sample average approximation and OPSW heuristic (Evers et al. 2014), an optimization model to address the trade-off between the number of stations and the coverage of the demand (Pinto et al. 2019), a Business Model Ecosystem (BMES) (Muhammad et al. 2018), a grey-DEMATEL based approach (Raj and Sah 2019), a pulse algorithm (Duque et al. 2015), adapting paths between reward nodes as travel times are revealed (Dolinskaya et al. 2018), an iterated local research (Gunawan et al. 2015a), a cluster search and cluster routes (Gavalas et al. 2013), a well-tuned ILS (Gunawan et al. 2015c), an artificial bee colony (Cura 2014), a biased-randomized selection process (Panadero et al. 2017), an enhanced ACO (Gambardella et al. 2012), a Variable Neighborhood Search (Campbell et al. 2011), an LP-based granular variable neighborhood search (Labadie et al. 2012), a Hybrid Variable Neighborhood Search and Simulated Annealing (Lau et al. 2012), an ILS (Souffriau et al. 2013), a fast SA and slow SA (Lin and Vincent 2012), a Variable Neighborhood Search (Zhang et al. 2014). The review of the literature is summarized in Table 1.

3 PROBLEM DEFINITION

In reality, for supply chain service providers operating in the same area, maximizing the total rewards collected by UAVs is crucial in the face of fierce competition. However, it is equally important to minimize the total distance traveled by the UAVs to ensure optimal efficiency. Additionally, ensuring that the UAVs do not run out of charge during their operations is a critical consideration. The problem addressed in this paper pertains to a stochastic multiobjective optimization for supply chain operations involving Unmanned Aerial Vehicles (UAVs). Equation 1 defines the objective functions as follows:

$$F(x,\nu) = \mathbb{E}\left[(R(x,\nu), D(x,\nu), O(x,\nu))\right] \tag{1}$$

where:

x: Represents the deterministic decision variables or solution vector.
ν: Represents the stochastic variables.

Table 1: Summary of literature review.

Reference	Characteristic	Stochasticity		Time Window		Stochastic Parameter			Charging Station		Algorithm
		Deterministic	Stochastic	Yes	No	Travel Time	Service Time	Reward	Yes	No	
(Sevkli and Sevilgen 2010)	OP	√			√	-	-	-		√	Strengthened Particle Swarm Optimization
(ŞEVKLİ and SEVİLGEN 2010)	OP	√			√	-	-	-		√	Strengthened Particle Swarm Optimization
(Chekuri et al. 2012)	OP	√			√	-	-	-		√	Approximation Algorithm
(Liang et al. 2013)	OP	√			√	-	-	-		√	Multi-Level Variable Neighborhood Search
(Campos et al. 2014)	OP	√			√	-	-	-		√	Greedy Randomized Adaptive Search Procedure
(Grasas et al. 2016)	TOP	√			√	-	-	-		√	Integer L-shaped Algorithm
(Poggi et al. 2010)	TOP	√			√	-	-	-		√	Branch-cut-and-price algorithm
(Bouly et al. 2008)	TOP	√			√	-	-	-		√	Memetic Algorithm
(Muthuswamy and Lam 2011)	TOP	√			√	-	-	-		√	Discrete Particle Swarm Optimization
(Lin and Vincent 2015)	TOP	√			√	-	-	-		√	Multi-start Simulated Annealing
(Teng et al. 2004)	TOP	√			√	-	-	-		√	Iterated Local Search
(Tang and Miller-Hooks 2005a)	TOP	√			√	-	-	-		√	Exact and Heuristic Approaches
(de Armas et al. 2017)	TOP	√			√	-	-	-		√	ILS-based Approach
(Hu and Lim 2014)	TOP	√			√	-	-	-		√	Iterative Three-component Heuristic
(Labadie et al. 2011)	TOPTW	√		√		-	-	-		√	Hybrid Greedy Randomized Adaptive Search
(Duque et al. 2015)	OPTW	√		√		-	-	-		√	Pulse Algorithm
(Gunawan et al. 2015a)	OPTW	√		√		-	-	-		√	Iterated Local Search
(Gambardella et al. 2012)	TOPTW	√		√		-	-	-		√	Enhanced Ant Colony System
(Lin and Vincent 2012)	TOPTW	√		√		-	-	-		√	Fast SA and Slow SA
(Labadie et al. 2012)	TOPTW	√		√		-	-	-		√	LP-based Granular Variable Neighborhood Search
(Souffriau et al. 2013)	TOPTW	√		√		-	-	-		√	Iterated Local Search
(Gavalas et al. 2013)	TOPTW	√		√		-	-	-		√	Cluster Search Cluster Routes
(Hu and Lim 2014)	TOPTW	√		√		-	-	-		√	Hybrid Local Search and Simulated Annealing
(Cura 2014)	TOPTW	√		√		-	-	-		√	Artificial Bee Colony
(Gunawan et al. 2015c)	TOPTW	√		√		-	-	-		√	Well-Tuned Iterated Local Search
(Gunawan et al. 2015b)	TOPTW	√		√		-	-	-		√	Hybrid Simulated Annealing and Iterated Local Search
(Ilhan et al. 2008)	OPSP		√		√			√		√	Bi-objective Genetic Algorithm
(Campbell et al. 2011)	OPSTS		√	√		√	√			√	Variable neighborhood search
(Papapanagiotou et al. 2014)	OPSTS		√	√		√	√			√	Monte Carlo sampling
(Lau et al. 2012)	DSOP		√	√		√				√	Completion Probability Approximations
(Pinto et al. 2019)	DSOP		√	√		√			√		Network Design Model
(Muhammad et al. 2018)	DSOP		√	√		√			√		Digitizing the Business Model Ecosystem (BMES)
(Raj and Sah 2019)	TOP	√			√	-	-	-	√		Grey-DEMATEL Based Approach
This Paper	TOPTWCS		√	√		-	-	-	√		SA and comparing it with Two Heuristics

$R(x,v)$: Represents the rewards collected by UAVs. (Maximization)
$D(x,v)$: Represents the total traveled distance by UAVs. (Minimization)
$O(x,v)$: Represents the occurrences of UAVs getting out-of-charge. (Minimization)
$\mathbb{E}[\cdot]$: Denotes the expected value operator, considering the stochastic nature of the problem.

3.1 Stochastic Variables

In real-life applications, the behavior of UAVs can be unpredictable due to various stochastic factors. In this paper, the model considers three such factors:

- **Reward:** The reward associated with a UAV task can be stochastic as it may depend on random events or variables that cannot be predicted with certainty. For example, in a surveillance scenario, the reward can be the probability of detecting a target, which can be affected by factors such as weather conditions, time of day, and the target's movement. Similarly, in a package delivery scenario, the reward can be the probability of successfully delivering a package, which can depend on factors such as traffic conditions and the recipient's availability.
- **Service Time:** The time taken by the UAV to complete a task at each node can be stochastic due to the size, shape, and location of the delivery items, as well as the time required to process them.
- **UAV Speed:** The speed of the UAV is another stochastic factor considered in the model since it can fluctuate due to weather conditions, the UAV's battery status, and its load.

These factors are defined are listed in Table 2:

4 SOLUTION APPROACHES

This paper proposes four distinct approaches to address the problem: two heuristic methods, Simulated Annealing (SA), and SA integrated with Neural Networks (SA-NN). Details of these approaches are described as follows.

Table 2: Stochastic factors and their distributions

Factor	Distribution
Reward	Normal (*mu*, *sigma*)
Service Time	Exponential (*lambda*)
Speed	Uniform (40 mph, 60 mph)

4.1 K-means with Maximum Reward (KMR)

This heuristic comprises of two phases, namely, clustering and sorting. The clustering phase involves the utilization of k-means for classifying nodes into clusters. K-means clustering, a vector quantization technique from signal processing, is popularly used for cluster analysis in data mining. The objective of this technique is to partition n observations into k clusters, where each observation belongs to the cluster with the nearest mean, representing a prototype of the cluster (Wagstaff, Cardie, Rogers, Schrödl, et al. 2001). The number of clusters is equal to the number of UAVs, and each UAV is assigned a specific cluster.

In the sorting phase, a descending order of nodes is generated within each cluster based on their associated reward. According to this heuristic, the UAV will first navigate to the node with the highest reward and continue to the next highest reward until the end of the time window. Algorithm 1 provides the pseudocode for KMR.

Algorithm 1 K-means with Maximum Reward (KMR)

Require: Clustering Phase:
  for each node i **do**
    Perform k-means(i, NumberOfChargingStations, 'Distance', 'cityblock', Options)
  end for
  UAV selects nodes in descending order of reward within the available time window.
Ensure: Searching Phase:
  for each cluster c **do**
    for each node i in c **do**
      Sort nodes in c by descending reward: R_i
    end for
  end for
  Initialize $best \leftarrow [node(1)]$
  for $i = 2$ to NumberOfNodes **do**
    For each node $j > i$, if $R_j > R_i$, update $best \leftarrow [best\ j]$
  end for
  return $best$

4.2 K-means with the Shortest Distance to the Previous Node (KSD)

This heuristic consists of two phases. The first phase is identical to that of k-means with maximum reward (KMR). In the second phase, nodes within each cluster are sorted as follows: firstly, the node with the shortest distance to the hub is searched, and its index is placed into a vector. Then, among the remaining nodes in the same cluster, the node with the shortest distance to the previous node in the vector is searched and added to the vector. Based on this heuristic, the UAV will always navigate to the node that has the shortest distance to the node that it has just visited. KSD is similar to KMR, with the only difference being the sorting criteria in the second phase: KSD sorts nodes based on the shortest distance to the previously visited node, while KMR sorts nodes based on descending reward.

4.3 Simulated Annealing

Simulated Annealing is a probabilistic technique for approximating the global optimum of a given function. It is particularly useful for large, complex search spaces. The algorithm simulates the physical process of heating a material and then slowly lowering the temperature to decrease defects, thus minimizing the system energy. SA has been effectively used as a simulation-optimization approach in different applications including healthcare (Dehghanimohammadabadi et al. 2023), manufacturing (Seif et al. 2020), and supply chain (Juan et al. 2018), among many. SA is selected as a benchmark since it has been used in many routing problems. Algorithm 2 provides the pseudocode for SA.

Algorithm 2 Simulated Annealing (SA)

Require: Initial solution s, initial temperature T, cooling rate α
Ensure: Optimal solution s_{best}
  $s_{best} \leftarrow s$
  while $T > 0$ **do**
    Generate new candidate s_{new} by modifying s
    $\Delta C \leftarrow C(s_{new}) - C(s)$
    if $\Delta C < 0$ or $rand(0,1) < e^{-\Delta C/T}$ **then**
      $s \leftarrow s_{new}$
      if $C(s_{new}) < C(s_{best})$ **then**
        $s_{best} \leftarrow s_{new}$
      end if
    end if
    $T \leftarrow \alpha \times T$
  end while
  return s_{best}

It begins with an initial solution s, temperature T, and cooling rate α. It iteratively explores solutions, accepting improvements and sometimes worse solutions based on a probability determined by the current temperature and change in cost function ΔC. This probabilistic approach helps SA escape local optima. As the algorithm progresses, temperature decreases according to α, leading to a more deterministic search. It returns the best solution s_{best} found during exploration.

In the SA model, where there are I nodes and K UAVs, a solution is represented as an integer permutation of length $I+K-1$. Numbers greater than I serve as delimiters. For instance, with 10 nodes and 2 UAVs, the permutation length is $10+2-1=11$, as shown in Figure 2. This permutation includes the nodes and delimiters, where the delimiters indicate the division of nodes among the UAVs.

7	3	4	1	9	6	11	2	7	5	10	8
UAV-1 Route						Delimiter	UAV-2 Route				

Figure 2: Example of a solution representation for SA.

4.4 Simulated Annealing with Neural Networks (SA-NN)

The fourth approach, SA-NN, enhances Simulated Annealing (SA) by incorporating a Neural Network (NN) where NN is a substitute for the simulation model. After collecting observations from the model, these observations are trained to predict performance measures. For this project, separate NNs are trained for each of the discussed objective functions and then queried. This method significantly saves execution time, especially in stochastic models where replications are time-consuming. Using NNs can reduce the need for extensive computational resources typically required for numerous simulations.

Detailed descriptions of these methods follow in subsequent sections. As shown in Figure 3, this figure illustrates the difference between SA and SA-NN, where instead of a simulation model, an NN predicts the performance measure.

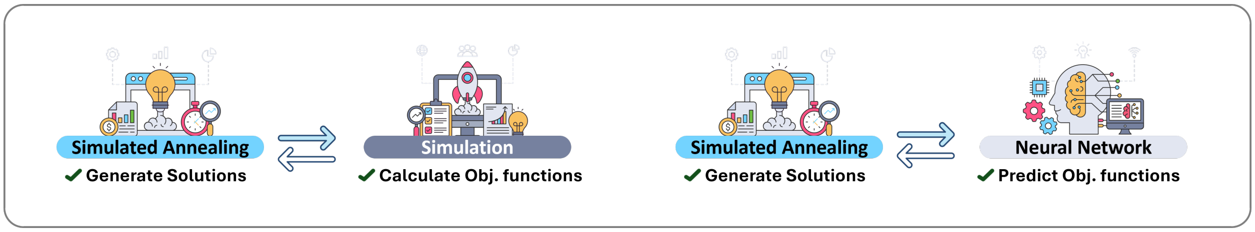

Figure 3: Comparison between SA and SA-NN approaches showing the substitution of the simulation model with a Neural Network for performance prediction.

5 EXPERIMENTAL RESULTS, COMPARISON, AND ANALYSIS

This section aims to assess the performance of the proposed models. Two experiments with two different numbers of nodes (n=30) and a complex model (n=60) are considered. The experiments were conducted on a machine with the following configuration: 32GB RAM, Windows 11, and an 8-core CPU. The neural network used in the experiments was a 3-hidden-layer (10,10,10) feedforward neural network.

In addition to objective functions defined in Equation 1, multiple other metrics are measured during the experiments including:

- **TOOC** (Total Time out of Charge): This metric represents the total time during which the UAVs are out of charge or unable to perform tasks due to battery constraints.
- **TTWV** (Total Time Window Violation): This metric quantifies the number of times the delivery was outside of the expected time window, indicating deviations from the desired schedule.
- **TR** (Total Reward): This metric measures the total reward accumulated by the UAVs during the routing process.
- **CR** (Coverage Ratio): The coverage ratio indicates the percentage of nodes covered during routing by the UAVs, providing insights into the effectiveness of the routing strategy.
- **TD** (Total Distance): This metric represents the overall distance covered by all UAVs to reach and service the nodes in the network.

For the experiment with 30 nodes, it is observed that both heuristics, KSD and KMR, consistently outperform SA-based approaches in terms of runtime, demonstrating their efficiency in solving the problem. However, the SA algorithm achieves the highest coverage ratio (CR) among all approaches, indicating its effectiveness in covering a higher percentage of nodes during routing. Additionally, the SA algorithm also achieves a lower total distance (TD) compared to other approaches, with higher total reward and 100% coverage rate, suggesting that it optimally minimizes the overall distance traveled by the UAVs to service the nodes (See Table 3).

The SA-NN approach improved the runtime of SA but apparently was not outperforming SA in terms of performance metrics. This is mainly due to the lack of training data or inadequate dataset for training. Even though the training set was increased from 10,000 to 100,000, it did not improve its efficiency. To address this, a new SA-based neural network model is applied in the next experiments.

Table 3: Comparative results of all approaches with 30 nodes (Replication size = 6).

Algorithm-Metric	**KSD**	**KMR**	**SA**	**SA-NN**
Runtime (s)	0.3	0.2	849.1	557.0
TOOC	0.0	3.0	0.0	4.0
TTWV	5.0	5.0	11.0	13.0
TR	1767.0	1645.0	1864.5	1403.2
CR (%)	96.7	76.7	100.0	73.3
TD	958.7	1183.3	1092.4	1326.2

Table 4: Comparative results of all approaches with 60 nodes.

Algorithm-Metric	**KSD**	**KMR**	**SA**	**SA-NN**	**SA-NN-Hybrid**
Runtime (s)	0.4	0.4	1155.7	654.1	704.2
TOOC	0.0	0.0	0.0	1.4	0.0
TTWV	12.0	12.0	25.0	20.2	27.0
TR	2328.6	1804.2	2803.8	1017.3	2388.5
CR (%)	66.7	36.7	76.7	33.4	63.3
TD	1203.6	1322.8	1400.0	1202.2	1494.3

In the second experiment, 60 nodes are considered, making the routing problem even more complex. This is mainly because the increased number of nodes leads to a larger solution space and more intricate routing paths. Results of this experiment are shown in Table 4.

A new approach called SA-NN-Hybrid is introduced to enhance the performance of the SA-NN approach. As depicted in Figure **??**, this hybrid approach combines the strengths of simulated annealing and neural network techniques. Initially, a portion of solutions (i.e., 50%) are predicted by a neural network to expedite the search process. Subsequently, the algorithm switches to a simulation model where actual performance values are generated for refinement and accurate metric estimations. This hybrid model enhances the SA-NN approach by leveraging the neural network's rapid solution generation and the simulation model's precise performance evaluation. The combination leads to improved efficiency and accuracy in finding optimal solutions.

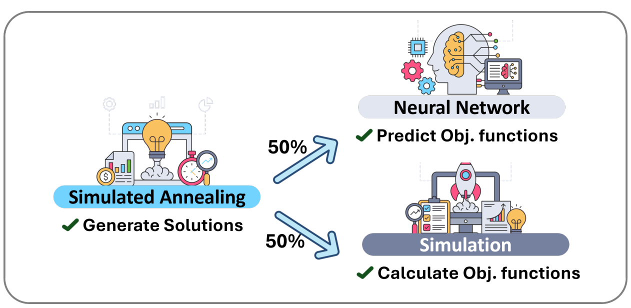

Figure 4: The SA-NN-Hybrid model uses a neural network to predict 50% of solutions, then switches to simulated annealing for refinement, enhancing performance.

While KSD and KMR algorithms exhibited comparable runtime, suggesting their efficiency in solving the problem within a short duration, their performance on other metrics is significantly lower than SA-based approaches. In general, SA outperformed all approaches with the highest reward (TR) and node coverage (CR = 76.7%) and without any out of charge incidents. This highlights the efficiency of SA to solve the model. Comparably, the new hybrid model achieved satisfactory similar performance with a lower runtime compared to SA, with almost a 40% reduction. This suggests that the hybrid approach effectively combines the strengths of simulated annealing and neural network techniques to achieve high-quality results.

6 CONCLUSION

The paper presents an experimental analysis of the Team Orienteering Problem for Unmanned Aerial Vehicles (UAVs) with Charging Stations, introducing four distinct approaches to enhance the UAVs' path planning and cruising capabilities. Initially, the study utilized two clustering-heuristic approaches: K-means with Maximum Reward or KMR and K-means with Shortest Distance or KSD. The research extends by incorporating advanced metaheuristic algorithms—Simulated Annealing (SA) and SA integrated with Neural Networks (SA-NN)—to refine the solution further.

The experiments conducted provide valuable insights into the performance of various algorithms in solving the Team Orienteering Problem for Unmanned Aerial Vehicles (UAVs). Across both experiments, it became evident that heuristic approaches, such as those employing the shortest distance and maximum reward strategies, showcased commendable efficiency, particularly in terms of runtime. However, as the complexity of the problem increased, optimization-based solutions, notably simulated annealing (SA), demonstrated superior performance, outperforming heuristic approaches in key metrics like total reward and node coverage. The introduction of SA-NN-Hybrid further emphasized the potential of hybrid techniques in enhancing algorithmic efficiency and solution quality. These findings underscore the importance of selecting appropriate algorithmic strategies tailored to the problem's complexity, with optimization-based approaches proving particularly effective for challenging scenarios.

This paper can be extended by considering other measures AI enables, such as simultaneous learning and optimization. In this approach, SA can optimize and NN can be utilized in a gradient-based version, and having these two models improve each other's performance iteratively. Additionally, exploring hybrid approaches that combine metaheuristic algorithms with machine learning techniques could be fruitful. For instance, integrating reinforcement learning with SA for adaptive path planning or employing genetic algorithms to evolve neural network architectures for better prediction accuracy.

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